Interpretation of Doppler Blood Flow Velocity Waveforms Using Neural Networks

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Doppler umbilical artery blood flow velocity waveform measurement is used in perinatal surveillance for the evaluation of pregnancy status. There is an ongoing debate on the predictive value of doppler measurements concerning the critical effect of the selection of parameters for the evaluation of doppler output. In this paper, we describe how neural network methods can be used both to discover relevant classification features and subsequently to classify patients. Classification accuracy varied from 92-99% correct.

INTRODUCTION

A major goal of perinatal medicine is to reduce perinatal morbidity and mortality [2, 7, 9]. Various noninvasive technologies are used in fetal surveillance. Umbilical artery blood flow velocity waveform (henceforth "umbilical artery waveform") measurement is one of these methods that is widely used in clinical practice (see Figure 1). However, a serious debate has focussed on the predictive value of doppler studies. The most critical issue is the parameters used. Such parameters generally include the Pulsatility Index (PI), Resistance Index (RI), and A/B (Systolic Diastolic) Ratio [6, 8, 11]. The exact biological meanings of these parameters are not clear.

One of our motivations for studying this subject is to explore feasibility of an automated system for classifying umbilical artery waveforms. Another one is to explore the possibility of using neural network learning methods to discover and use classification features. In particular, we apply a way in which an unsupervised learning method can be used to discover key data features that can serve as input to a supervised pattern classification model.

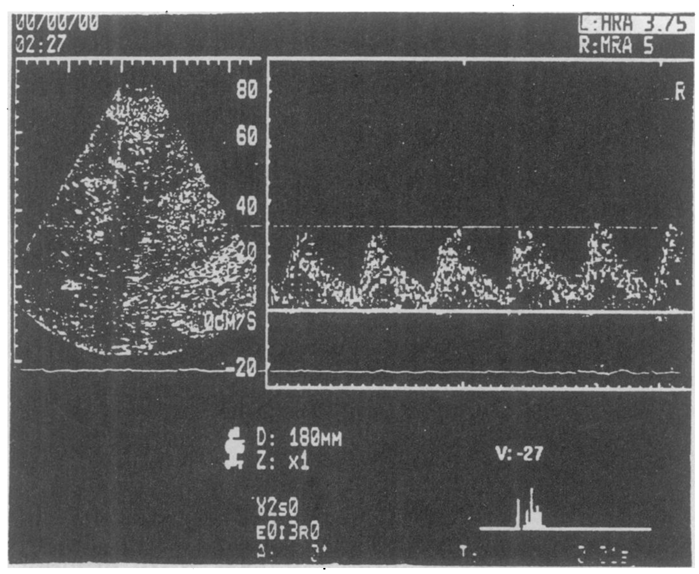

Figure 1: Example doppler waveform.

In this study, we used two different neural network methods for the development of an automated system for the analysis of umbilical artery waveforms. First, a modified Kohonen's self organizing feature map (SOFM) algorithm [5] is used for automatic feature extraction and clustering of the preprocessed doppler signal. Map features are then used as input to a back propagation training algorithm to classify an umbilical artery waveform as normal, abnormal or suspicious. The test results obtained by our model are compared directly with actual patient outcome (i.e., not

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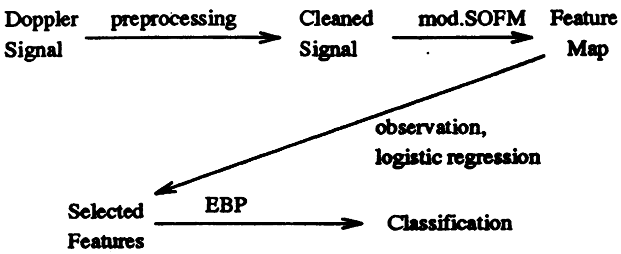

Figure 2: Procedure used in this study.

with physician classification of the waveform).

METHODS

The main steps in interpretation of doppler umbilical artery waveforms include preprocessing, map formation, feature extraction, feature selection and classification respectively (see Figure 2).

Preprocessing Waveforms

Umbilical artery waveforms are acquired by a 3.75 MHz duplex pulsed wave doppler probe during the data acquisition phase. Doppler images are then transferred from ultrasound to computer environments by means of a frame grabber. Averaging, thresholding edge detection, smoothing and image clearing are the main processes in the course of image analysis. For feature extraction, filtering algorithms are applied to digital waves in order to reduce noise which is inherent to doppler equipment and to the process of digitization of analog images. Averaging using a sliding window technique is first applied to umbilical artery waveforms within the thresholding process. Waveforms are further enhanced from the background by global thresholding. The edge of an umbilical artery waveform is detected by using Robert's Gradient operator [3]. Then, 4x4, 4x3, 3x4 & 3x3 masks are used to smooth and clear umbilical artery waveform signals to remove irrelevant details coming from the background of raw images and render waveforms more recognizable and crisp in form as seen in the Figure 3.

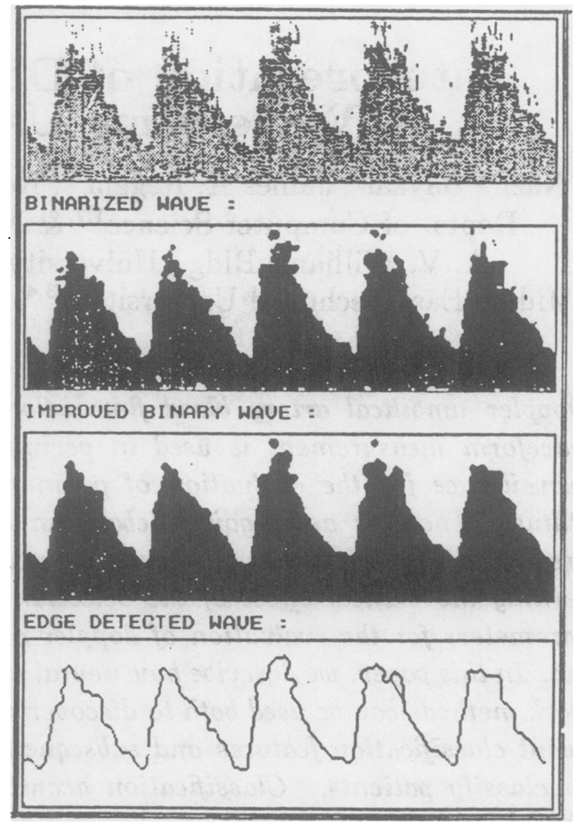

Figure 3: Preprocessing steps of BFVWs.

Map Formation with a Modified SOFM

Kohonen's SOFM is an unsupervised learning algorithm [5] that modifies the internal state of the neural network in order to model features found in the training data. No training response is prespecified for any training input. In this study, a modified SOFM is used for map formation and automatic feature extraction. Our algorithm is similar to SOFM except for a parameter ϕ in the learning rule:

$$w_i(t+1) = w_i(t)+\alpha(t)\phi(t)(x_i(t)-w_i(t)).$$

Excitation term $\phi(t)$ is defined to be

$$\phi = (\gamma - \mu)/\gamma \quad \text{where;}$$

γ = topological radius of neighborhood, and

μ = topologic distance from winner.

Input vectors to the SOFM are the preprocessed umbilical artery waveform signal patterns. This input space has dimension 300 which is the length of the processed signal.

Figure 4: Schematic illustration of map.

			S	S						
			S	S	N	N				
	S	S	S		N	N		N	N	N
	S	S	S		N	N		N	N	N
					N	N				
	A	A	A				A	A		
	A	A	A				A	A		
	A	A	A							

The output of the system is an 11x11 array of processing units. Initially, all of the incoming connections to the output nodes are assigned small random weight values and the rate of weight tuning is 0.5. During learning a set of training umbilical artery waveform signals are shown to the network.

At the end of the training process we obtained six different clusters of umbilical artery waveforms as shown in Figure 4. The map elements are labeled as N (normal) S (suspicious) or A (abnormal) if the most of the waveforms mapped onto it have actual outcome normal, suspicious or abnormal respectively.

Feature Extraction

Various different indices have been used for quantitative assessment of umbilical artery waveforms. The most commonly used indices are the Pulsatility Index (PI), ABR (A/B ratio, Systolic/Diastolic ratio) and the Resistance Index (RI) [2, 9, 10, 8] defined as:

$$PI = (A - B)/Mean$$

$$ABR = A/B$$

$$RI = (A - B)/A$$

A, B and Mean are shown in Figure 5. From the automatic feature extraction and clustering phase and previous studies we observed that these indices are inadequate to evaluate umbilical artery waveforms [1]. For this reason, we extracted features from the normal, abnormal and suspicious clusters. We observed the general signal form and differences between waveforms from cluster to cluster and between pregnancy weeks. We identified features such as slope, fetal pulse rate, pulse width, peak values from FFT (fast Fourier transform) of the signals, A-B and pregnancy week that correlated with specific classes. Starting with 11 initial parameters, we used step-down logistic regression [4] to identify seven important and linearly independent features: A-B, ABR, FFT, slope, fetal pulse rate, pulse width and pregnancy week. Note that only one of the features discovered in this fashion (ABR) is among the three most widely used features described above.

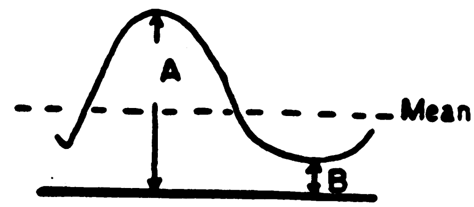

Figure 5: Widely used BFVW parameters.

Application of Error Back Propagation

The input vector represents the seven computed new parameters of umbilical artery waveforms. The network structure used in our experiments has one input, one hidden, and one output layer. The output layer has three nodes corresponding to classes normal, suspicious and abnormal.

We performed experiments on approximately 600 umbilical artery data sets having different gestational weeks belonging to 199 normal and high risk pregnancies. Patients are observed for their clinical conditions during the pregnancy period and they get an outcome grade between 0 and 5 for the worst and best case, respectively. Experimental data consists of multiple recordings from each of 56 abnormal (outcome grade less than 2.5), 88 suspicious (outcome grade between 2.5 and 3.8) and 55 normal (outcome grade between 3.9 and 5) patients' waveform. Clinically, data acquisition starts with the 14th gestational week and continues every four weeks. The data from weeks 14 to 40 were separated into seven groups. Clustering and feature extraction enable us to find out the common similarities within each gestational week group and then these groups are trained independently. Observed clinical conditions and outcome grade of the patient are used as the basis of classification criteria (i.e., not a direct physician classification of the waveform). Normal classification is assigned for outcome grade between 3.9 and 5 and pregnancy condition has one of the following a) normal pregnancy, normal outcome (ideal normal); b) normal but undesirable condition may exist; and c) normal, bad obstetrical history. Abnormal classification is assigned for outcome grade between 0 and 2.4 and if there are a) fetal problems; or b) perinatal and intrapartum problems and bad outcome. Pregnancy condition and outcome that do not belong to any of these classifications are labeled suspicious. According to these situations, computed features of the umbilical artery waveforms from patients having known outcome are choosen as the desired values of our error back propagation algorithm.

RESULTS

The basic result of this study is the reliable interpretation of umbilical artery waveforms for fetal well-being. Our simulation results are compared with the actual outcome and results are shown on the Table 1. Column GW records gestational weeks of data collecting for each group. TRAIN P# (TEST P#) is the number of training (test) patterns used for each group. Training cases were selected if they were good representations of their cluster (Figure 4); test cases were randomly selected (except training cases were excluded). Correct classification CORR is computed by

Table 1: Classification results.

GW	TRAIN P#	TEST P#	CORR.
14-15	20	40	92.50%
16-19	30	60	95.00%
20-23	40	60	96.67%
24-27	40	70	98.57%
28-31	40	60	98.33%
32-35	40	60	98.33%
36-40	30	50	96.00%

$$(100 * c)/t$$

where; c = the number of umbilical artery waveforms that are classified the same as actual outcome; and t = the total number of test samples of the same gestational week.

In our simulations, we used a different set of patients including normal and high risk pregnancies (number in each class varies between 6 to 27) for training and testing for each gestational weeks as shown in Table 1. Sensitivities and specificities for classification performance run between 83.33% to 100% for each group.

As seen from Table 1, at the beginning of the pregnancy less accurate results are obtained. The main reasons for this situation may be less training data; and the normal (ideal) form of the signal changes very much from patient to patient.

DISCUSSION

Blood flow velocity waveform measurements are widely used in perinatal surveillance [6, 8]. Different fetal blood vessels are used to evaluate fetal health. Umbilical artery waveform measurement is the most popular one in doppler studies. Good blood flow in the umbilical artery reflects good oxygenation of the fetus, and is of vital importance.

Various parameters are used for the interpretation of doppler waveforms. However, there are no clear cut criteria to evaluate doppler waveforms. This situation has motivated us to develop an automated system for the reliable evaluation of umbilical artery waveforms for perinatal surveillance. In the literature, Pulsatility Index (PI), Resistance Index (RI) and A/B ratio are the main parameters in clinical practice, although they are highly correlated with each other. The heterogeneity of doppler technology and probable interindividual variation of semi-automated determination of doppler parameters are also important issues in obtaining accurate results. Another critical issue is the representative meanings of doppler indices.

Based on the remarkable accuracy of our system predictions, we conclude that an automated system for classification of umbilical artery waveform is feasible and shows high correlation with outcome. Further, the unsupervised modified SOFM method proved to be a very powerful approach to discovering key features in a complex data. Our system may become an automated preliminary report and decision assistance. In addition, seven features of umbilical artery waveforms were discovered that had strong predictive power. These features deserve further study in a prospective fashion.

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